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Transfer of Statistical Learning Between Tasks

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Recent studies have shown that observers can learn to suppress locations in the visual field with a high distractor probability. Here, we investigated whether this learned suppression resulting from a spatial distractor imbalance transfers to a completely different search task that does not contain any distractors. Observers performed the additional singleton task and learned to suppress the location that was likely to contain a color singleton distractor. Within a block, the additional singleton task would randomly switch to a T-among-L task where observers searched in parallel (Experiment 1) or serially (Experiment 2) for a T among Ls. The upcoming search was either unpredictable (Experiment 1/2A) or cued (Experiment 1/2B). The results show that there was transfer of learning from one to the other task as the learned suppression stayed in place after the switch regardless of whether the T-among-L task was performed via parallel or serial search. Moreover, cueing that the task would switch had no effect on performance. The current findings indicate that implicit learned biases are rather inflexible and remain in place even when the task and the required search strategy are dramatically different and even when participants can anticipate that a change in the search required is imminent. This transfer of the suppression to a different task is consistent with the notion that suppression is proactively applied. Because the location is already suppressed proactively, that is, before display onset, regardless which display and task is presented, the suppressed location competes less for attention than all other locations.

Public Significance Statement

We are able to extract regularities that are present in our environment allowing us to learn to suppress those locations that often contain distractors. The current study shows that the suppression that was learned in one search task stays in place if we switch to another search task, even when this task requires a completely different type of search. The findings are remarkable as they are inconsistent with generally agreed claim that implicit statistical learning is highly task specific with little to no transfer across tasks.

Keywords: visual attention, statistical learning, task switch, spatial priority map

A whole host of recent studies have demonstrated the importance of statistical learning in optimizing attentional selection priorities during visual search (for a review, see Theeuwes et al., 2022). The underlying notion is that through statistical learning, attentional selection is facilitated as you learn to direct attention to those events that have proven to be important in the past and suppress those that were distracting. Statistical learning is often considered to be an implicit and unconscious cognitive process in which repeated patterns, or regularities, are extracted from the sensory environment (Frost et al., 2019; Turk-Browne et al., 2005).

Findings regarding statistical learning and attention have demonstrated that observers are able to learn regularities concerning the search target as they are able to prioritize specifically those locations that are more likely to contain a target (Shaw & Shaw, 1977). For example, Geng and Behrmann (2002) conducted so-called probability cuing studies, and showed that response times (RTs) were reduced for discriminating targets appearing at more probable locations compared to less probable locations within the visual field (see also Duncan et al., 2023; Geng & Behrmann, 2005; Huang et al., 2022). In contextual cueing studies, it was shown that searching for a target was facilitated when it appears in a visual layout that was previously searched relative to visual layouts that were never seen before (Chun & Jiang, 1998). Typically, in these studies, participants are required to search for a "T" target among "L" distractors in sparsely scattered display configurations. Half of the display configurations are repeated across blocks while others are encountered only once. The classic result is that participants are faster in finding targets when they appear in repeated configurations than in configurations that they have not seen before,

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suggesting that participants have learned the association between the spatial configuration and the target location (for a review, see Goujon et al., 2015).

Recently, several studies revealed that participants cannot only learn the regularities regarding the task-relevant target but also regarding the task-irrelevant distractor. In a series of experiments B. Wang and Theeuwes (2018a, 2018b, 2018c) used a variant of the additional singleton task and showed that through statistical learning, attentional capture by the salient distractors was significantly reduced (for similar finding, see Ferrante et al., 2018; Goschy et al., 2014; van Moorselaar & Theeuwes, 2022). Typically, in experiments like these, participants search for a salient shape singleton (i.e., a diamond between circles or a circle between diamonds) while they are required to ignore a colored distractor singleton that is highly salient. Unbeknownst to the observers, the salient distractor appears with a higher probability in one location than in all other locations. Without actually being aware of it, the results show that participants learn the spatial imbalance of distractor positions as evidenced by less attentional capture by the salient distractor when it appears at a high-probability location relative to low-probability locations. In addition, it is often found that this effect is accompanied by less efficient selection of the target when it happens to appear at the high-probability distractor location (e.g., van Moorselaar & Theeuwes, 2021)

These findings have been explained by assuming that through learning, the weights within the assumed spatial priority map are continuously adjusted. The weights within the spatial priority map dynamically control the deployment of covert attention and gaze (Theeuwes et al., 2022). When a location contained relevant information in the past, the weight representing that location is upregulated, whereas a location is downregulated when it has a higher probability of containing distracting information. In this view, selection simply follows the priority landscape that arises after combining a variety of signals, including top-down goals, bottom-up saliency, and priority weights induced by previous selection episodes (Theeuwes, 2019). Notably, subsequent studies indicated that this type of statistical learning occurs without much effort (Duncan & Theeuwes, 2020; Gao & Theeuwes, 2020), largely occurs outside awareness (B. Wang & Theeuwes, 2018a), and is not influenced by explicit knowledge of the regularity (Gao & Theeuwes, 2022).

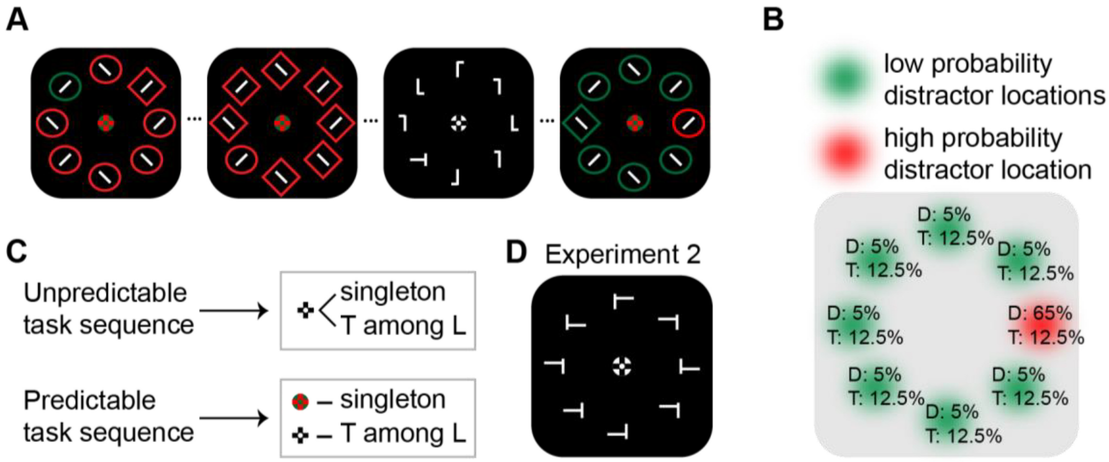
One aspect that has not been systematically investigated is whether statistical learned suppression learned in one search task transfers to another search task. A study by Britton and Anderson (2020) examined whether learned spatial suppression established within the additional singleton paradigm transferred to a modified version of the spatial cueing paradigm, wherein a spatial cue predicted the location of an upcoming target character at chance level. The absence of transfer, as indexed via the cuing effect, observed in that study may not be surprising given that top-down attention generated by the cue arguably overrides any attentional bias implemented by statistical learning (Dolci et al., 2023), leaving it unclear whether suppression learned in one task remains in place in a different task setting. Nevertheless, there is reason to assume that this may be the case, as probability cueing studies (cf., Geng & Behrmann, 2002) have shown that learned facilitation does transfer between tasks. For example, in a study by Jiang et al. (2015) during the initial training phase, participants learned in which quadrant of the screen the target was more likely to be presented. After establishing an attentional bias toward the high-probability quadrant (i.e., probability cuing), in a subsequent testing phase in which a different search task was employed, the target appeared with equal probability in all quadrants. It was demonstrated that the learned attentional bias remained in place when transferring from one to another task, as long as these tasks both relied in (serial) guided search (e.g., T among Ls to 2 among 5 s, and vice versa), suggesting that the same priority map was used in different search tasks. By contrast, there was no transfer from one to the other task when one task required serial (conjunction) search and the other parallel (feature) search. The absence of transfer was attributed to the presence of a perceptually salient cue that may have overshadowed learning of the probability cue, an argument that could also be used to explain the null finding in the one study that examined this issue within the context of learned distractor suppression (Britton & Anderson, 2020). Thus, while there is reason to assume that under specific conditions a learned attentional bias may transfer from one task to another, to date it remains unclear whether learned suppression generalizes from one task to the other.

Although only a single experiment thus far examined transfer of learned distractor suppression across tasks, there are a few studies examining the relationship between learned suppression and the context within which learning took place. On the one hand, there is evidence suggesting that spatially learned suppression can be implemented in a context-dependent fashion. Turatto et al. (2018) showed that the reduction in attentional capture by irrelevant onsets relied on a stored representation in relation to their context. Relatedly, Gao et al. (2023) showed that learned suppression was specific to the display configuration in which learning took place. Such context specificity effects are consistent with the notion that attentional control resulting from selection history is not necessarily inflexible and slow to adjust, but can be adjusted rapidly in response to specific display characteristics and their learned associations (Crump et al., 2018; C. Wang et al., 2023). While this research suggests that it is unlikely that learning will transfer between two distinct search tasks, other research has shown that the context wherein learning took place is not tied to the learned suppression (Britton & Anderson, 2020; de Waard et al., 2022), which make a possible transfer of learning between tasks more likely. In these studies, suppression observed in one context (defined by a background image) generalized to another context, and vice versa, suggesting that the association between background and the specific high-probability location within the search display was not learned (but see de Waard et al., 2023).

The current study was designed to examine whether suppression resulting from a spatial distractor imbalance would transfer to another search task without any distractors. For this purpose, within blocks, we combined the additional singleton task, where observers search for a unique shape while ignoring a salient color distractor singleton, with a T-among-L search task. The basic procedure is illustrated in Figure 1. The color distractor singleton was presented much more often in one location than in all other locations, whereas targets in both tasks (i.e., unique shape in singleton task and T in T-among-L task) were equally distributed among all search positions. The predictions are straightforward: if there is transfer of learning from the additional singleton task to the T-among-L task, we expect that if the target T is presented at a location that is the high-probability location during the additional singleton, participants should be slower to respond. However, if there is no transfer of learning then we expect that the response to the target T is equally fast across all locations is the visual field.

Given that Jiang et al. (2015) found no transfer between tasks that required a switch in search strategy (from parallel to serial search and vice versa), we created two T-among-L searches: one in which the T

Figure 1
Experimental Paradigm



Note. (A) Example trial sequence. Following a fixation display, either the additional singleton paradigm appeared, in which participants had to indicate the orientation of the line inside the unique shape, or the T-among-L task appeared, in which participants had to indicate the orientation of the T. (B) Schematic representation of the spatial regularities of the distractor (location counterbalanced across participants). Percentages at each location represent the probabilities of the distractor (D) and the target (T) appearing at a given location within each task. (C) The upcoming task either varied unpredictably across trials (Experiments 1A and 2A) or was cued by the colors within the fixation point already prior to search display onset (Experiments 1B and 2B). (D) In Experiment 2, the characteristics of the T-among-L task were changed. Specifically, the L-shaped items were rendered more similar to the target T so that search could no longer be conducted in parallel, but instead had executed by serial search. See the online article for the color version of this figure.

could be found by means of parallel pop-out search and one that required slow serial search (see Figure 1). Also, within a block, we either switched unpredictably from the additional singleton task (in which learning took place) to the T-among-L task or we cued the upcoming search task in advance. It is feasible that when the switch is unpredictable, there is transfer between the tasks because the spatial priority map that is shaped during additional singleton search stays in place when there is an unexpected switch to the T-among-L task. Therefore, we ran additional experiments in which a cue would indicate that the task would switch from additional singleton search to the T-among-L search, and vice versa. This cue should operate as an explicit attentional goal to abandon the spatial bias that was learned during additional singleton search (see Zhang & Carlisle, 2023)

Transparency and Openness

We report how we determined our sample size, all data exclusions (if any), all manipulations, and all measures in the study. All data, analysis code, and research materials are available on the Open Science Framework page (https://osf.io/tdgwf/). Data were analyzed using Python 3 (Guido & Drake, 2009). This study's design and its analysis were not preregistered. Data were collected in 2023.

Experiments 1A and 1B

Method

Participants

As the current study was the first to examine the transfer of learned suppression from one search task to another, the estimated effect size could not be based on previous literature. Therefore, we chose to be cautious and use a medium effect size ($d = 0.4$; even though effect sizes in comparable statistical learning studies are typically larger; e.g., context studies by Britton & Anderson, 2020; de Waard et al., 2022 reported effect sizes >0.5) in an a priori power analysis for two-tailed paired sampled t tests. In combination with an α level of .05, and a power of .80, G*Power (Faul et al., 2007) suggested that a sample size of at least 52 was required to detect a significant effect. Based on this we chose to collect 56 participants in each study so that the high-probability distractor location could be counterbalanced across participants.

Participants were recruited via the online platform Prolific (https://www.prolific.co; £3.75). Prior to the experiments, which were conducted online on a JATOS server (Lange et al., 2015), participants provided digital informed consent. Datasets were only analyzed when an experiment was completed in full. The ethical committee of the Faculty of Behavioral and Movement Sciences, Vrije Universiteit approved the study, which was conformed to the Declaration of Helsinki. The final samples ($N = 56$) in Experiment 1A ($M_{age} = 28$, range = 19–39; 13 female) and Experiment 1B ($M_{age} = 30$, range = 20–40; 16 female) were obtained after excluding respectively three and four participants identified as outliers (based on overall accuracy [$N = 2$ in Experiments 1A and 1B] and reaction time [RT; $N = 1$ in Experiment 1A; $N = 2$ in Experiment 1B]; >2.5 *SD* from the group mean).

Task, Stimuli, and Procedure

As the experiment was conducted online, we had little control over the experimental setting, and for replication purposes, we thus report pixel values to describe the stimuli. The experiment was created in OpenSesame v3 (Mathôt et al., 2012) using OSWEB (Version 1.4).

Each trial started with a 500-ms black fixation display, in which a black and white circular fixation point as designed by Thaler et al. (2013) was shown at the center of the screen. Subsequently, a search display appeared, in which eight equally spaced stimuli, appeared on an imaginary circle around fixation (radius = 200 pixels; see Figure 1A). In one variant of the search display, based on the additional singleton paradigm, the display consisted of either one circle (radius = 35 pixels) among diamonds (40 × 40 pixels) or vice versa. These stimuli, whose outline could either be colored red or green, all contained a white line tilted 45° either to the left or to the right (counterbalanced within search displays). Participants were instructed to report the orientation of the line inside the unique shape via button press (left and right arrow keys). On a subset of trials (71%) one of the homogenous shapes was assigned a unique color (e.g., if the shapes were green, the distractor was red, or vice versa) rendering it a colored singleton distractor. Critically, this colored distractor appeared with a higher probability (65%) on one of the search locations (counterbalanced across participants) rendering this location a high-probability distractor location (Figure 1B). In the other search display variant, the display contained one white T (78 × 52 pixels) among seven Ls (78 × 26 pixels). These Ls were randomly rotated along the vertical and/or horizontal axis, with the restriction that each unique L character was present at most two times in the display. Participants were instructed to indicate via button press whether the target T was rotated left or right. Critically, in both variants of the task, the target (shape singleton or letter T) appeared with equal probability across all eight locations (Figure 1B). In the singleton task this was accomplished by having the target appear with equal probability across all eight locations both in distractor-present and distractor-absent displays. The search display remained visible until response, with a timeout of 2,000 ms. In case of an incorrect response, a red X was shown at fixation for 250 ms.

The critical difference between Experiments 1A and 1B was that in Experiment 1A the circular fixation point remained black and white throughout the entire experiment, whereas in Experiment 1B the colors of the fixation point signaled the upcoming search task (see Figure 1C). Specifically, on singleton search trials, the fixation point was a green and red cross, whereas it was in white and black for trials that required search for a T among Ls. Participants were explicitly informed about characteristics of the two cue types, and the upcoming tasks that these cues signaled.

Participants were instructed to keep their eyes at fixation, and to indicate the orientation of the target (the line inside shape singleton or T) as fast as possible, while trying to keep the number of errors to a minimum. At the start of the experiment, participants first practiced the additional singleton paradigm and the T-among-L task in separate practice blocks (15 and 10 trials respectively) followed by a practice block in which trials from these individual practice blocks were randomly combined. Practice blocks were repeated until mean accuracy was above 66% and mean RT was below 1,100, 1,000, or 900 ms in respective practice blocks. The 10 subsequent experimental blocks all contained 56 additional singleton trials and 32 T-among-L trials randomly intermixed, except for the first experimental block which only contained the additional singleton paradigm. At the end of each block, participants received feedback on their performance (i.e., mean RT and accuracy). After the last block, participants were asked to indicate whether they had noticed that one of the locations contained the distractor with higher probability (yes or no), and then to indicate this location.

Statistics

Search times analyses were limited to data of correct trials only. RTs were filtered in a two-step trimming procedure: trials with RTs shorter than 200 ms were excluded, after which data were trimmed based on a cutoff value of 2.5 *SD* from the mean per participant per search condition. Exclusion of incorrect responses (8.6% in Experiment 1A; 8.0% in Experiment 1B) and data trimming (2.8% in Experiment 1A; 2.6% in Experiment 1B) resulted in an overall loss of 11.4% and 10.7% of trials in Experiments 1A and 1B, respectively. Remaining RTs were analyzed with repeated measures analyses of variance (ANOVAs), where reported p values are Greenhouse–Geisser corrected in case of sphericity violations, followed by planned comparisons with paired t tests using JASP software (JASP-TEAM, 2024). As an effect size in paired sample comparison, we report Cohen's d_z, which reflects the standardized mean difference effect size for within-subjects designs.

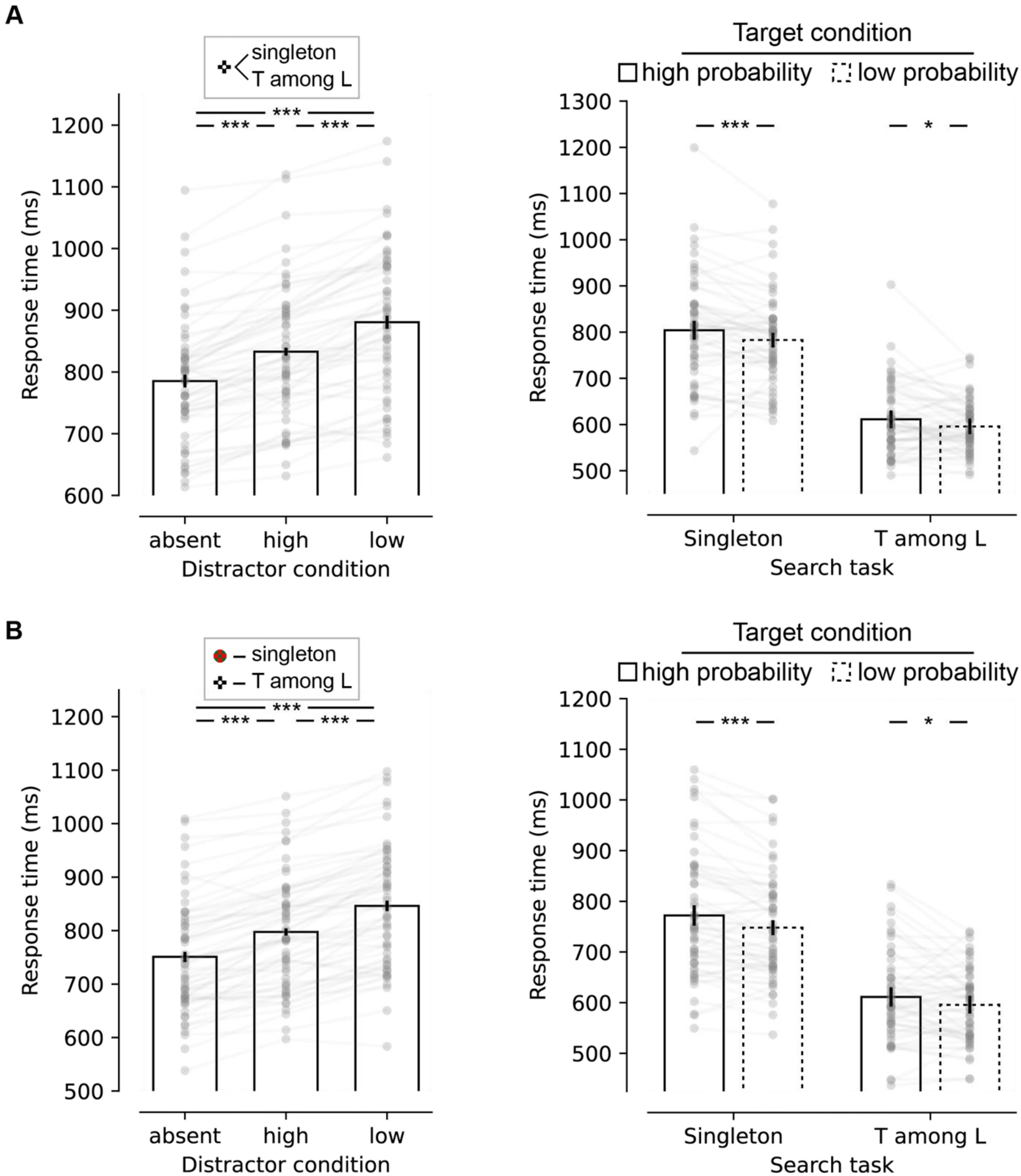
Results

As a first step, we examined whether the spatial distractor imbalance resulted in reduced distractor interference at high-probability distractor locations. For this purpose, we entered RTs into a repeated measures ANOVA with within-subject factor distractor condition (no distractor, low-probability distractor, high-probability distractor) and Experiment (1A and 1B) as a between subjects factor, which yielded a main effect of distractor condition, $F(1.6,\ 178.6) = 337.9$, $p < .001$, $\eta_p^2 = .75$. Although numerically, overall responses were faster when the upcoming search display could be predicted this was not reflected in a main effect of experiment ($F = 2.9$, $p = .09$). As visualized in Figure 2 (left panels in subplots A and B), irrespective of whether the singleton task was not cued or cued, distractors reliably slowed responses both at low- and high probability distractor locations. Experiment 1A; main effect distractor condition: $F(2,\ 86) = 158.8$, $p < .001$, $\eta_p^2 = .75$, or cued, Experiment 1B; main effect distractor condition: $F(2,\ 92) = 180.5$, $p < .001$, $\eta_p^2 = .77$, distractors reliably slowed responses both at low, $t(55) = 14.45$, $p < .001$, $d = 1.93$ in Experiment 1A; $t(55) = 15.87$, $p < .001$, $d = 2.1$ in Experiment 1B, and high-probability distractor locations, $t(55) = 10.51$, $p < .001$, $d = 1.40$ in Experiment 1A; $t(55) = 10.84$, $p < .001$, $d = 1.45$ in Experiment 1B. Critically, distractor interference was less pronounced at high-probability distractor locations relative to low-probability locations, $t(55) = 10.2$, $p < .001$, $d = 1.37$ in Experiment 1A; $t(55) = 10.63$, $p < .001$, $d = 1.42$ in Experiment 1B.

Having established that distractor interference reduced at high-probability distractor locations, consistent with the idea that learning about distractor regularities results in suppression of that location (B. Wang & Theeuwes, 2018a; Ferrante et al., 2018; van Moorselaar & Theeuwes, 2021), we next examined how this spatially tuned suppression affected target processing. To allow for a comparison between the singleton and the T-among-L task, this analysis only included distractor-absent displays from the singleton task. As visualized in Figure 2 (right panels in subplots A and B), despite being equally prevalent across all locations, targets were detected slower at the high-probability distractor location, not only in the singleton task, but also in the T-among-L task, and critically this happened irrespective of whether the characteristics of the upcoming search display either varied unpredictably (Experiment 1A) or were cued in advance (Experiment 1B). A repeated measures ANOVA with within-subjects

Figure 2

Learned Spatial Suppression Transfers to Another Task That Does Not Require Distractor Suppression



Note. (A) Mean RT in the singleton task as a function of distractor condition (left plot) and as a function of search task (singleton task, T-among-L task; right plot) and target condition (high probability and low probability) in Experiment 1A, where tasks varied unpredictably. (B) The same analysis was demonstrated in Panel A, using data from Experiment 1B, where the fixation marker signaled the upcoming search task such that it could be anticipated. All error bars here and in subsequent plots represent 95% within-subject confidence intervals (Morey, 2008). RT = reaction time. See the online article for the color version of this figure. * $p < .05$. *** $p < .001$.

factor search task (singleton task, T-among-L task) and target condition (high probability, low probability; where target locations were artificially coded as high and low based on the distractor regularity in the singleton task) and Experiments (1A and1B) as a between subjects factor, confirmed that target detection was impaired at high-probability distractor locations, main effect target condition: $F(1, 110) = 26.9$, $p < .001$, $\eta_p^2 = .20$; $F(1, 55) = 12.5$, $p < .001$, $\eta_p^2 = .19$ in Experiment 1A; $F(1, 55) = 14.49$, $p < .001$, $\eta_p^2 = .21$ in Experiment 1B, and this effect did not interact with experiment, $F = 0.04$, $p = .85$. Planned pairwise comparisons demonstrated that the effect was not only reliable in the singleton task, $t(55) = 3.02$, $p = .004$, $d = 0.40$ in Experiment 1A; $t(55) = 4.12$, $p < .001$, $d = 0.55$ in Experiment 1B, but also in the T-among-L task, $t(55) = 2.22$, $p = .03$, $d = 0.30$ in Experiment 1A; $t(55) = 2.16$, $p = .035$, $d = 0.29$ in Experiment 1B. Together these findings show that learned spatial suppression in one search task, will transfer to another search task, even when that second task is randomly repeated, or can be anticipated.

To examine whether the observed spatial biases were driven by explicit knowledge, at the end of the experiment participants were asked to indicate whether they noticed the spatial imbalance, and to indicate which location contained a higher distractor probability. Out of the 22 participants (12 in Experiment 1A and 10 in Experiment 1B) who indicated that they noticed the spatial imbalance, only nine (four in Experiment 1A, five in Experiment 1B) correctly identified the high-probability location. While our questionnaire is not sensitive enough to determine whether or not participants were aware of the distractor manipulation (Vadillo et al., 2020), we take these results to reflect that the learned distractor suppression in the singleton task, and the resulting transfer to the T-among-L search, should not be attributed to a deliberate search strategy, but instead reflects implicit statistical learning.

Experiment 2

Although the results from Experiment 1 showed that a learned attentional bias learned within one task, transfers to another search task, even when the characteristics of the upcoming search display could be predicted, it should be noted that the type of search required was the same in both tasks as the target could be detected by means of parallel search across the display. In other words, in both tasks, the target was clearly distinct from the surrounding search elements, and priority signals reliably guided attention toward the target (Liesefeld & Müller, 2020). This leaves open the question whether transfer of learned spatial probabilities is restricted to search tasks that favor the same search strategy or whether it is also observed when the underlying search mechanisms clearly differ between tasks. To examine this, in Experiment 2, we investigated whether we would observe the same transfer, when the T-among-L task could no longer be conducted in parallel, but instead required serial search.

Method

The methods of Experiment 2 were identical to those of Experiment 1 except for the following changes.

Participants

The final samples in Experiment 2A ($N = 56$, $M_{age} = 29$, range = 18–40; 22 female) and Experiment 2B ($N = 57$, $M_{age} = 29$, range = 19–39; 18 female) were obtained after excluding respectively four and one participants identified as outliers (based on overall accuracy [$\pm$2.5 *SD* from the group mean]).[1] In Experiment 2B outlier selection was preceded by removing all participants ($N = 5$) with mean accuracy below 65% as visual inspection of the data revealed that participants with near-chance performance were otherwise not selected as outliers.

Task, Stimuli, and Procedure

Critically, to induce a change in search strategy in the T-among-L task (i.e., induce serial search), L-shaped distractors were created by shifting the base of the T-shaped characters 15 pixels away from the center (in either direction), such that T no longer clearly stood out from the L-shaped filler items (see Figure 1D). Also, the timeout to respond was extended to 3,000 ms, and RT thresholds during the three practice blocks were set to 1,100, 3,000, and 1,200 ms, respectively. Exclusion of incorrect responses (12.5% in Experiment 2A; 12.0% in Experiment 2B) and data trimming (8.3% in Experiment 2A; 7.4% in Experiment 2B) resulted in an overall loss of 20.7% and 19.4% of trials in Experiments 2A and 2B, respectively.

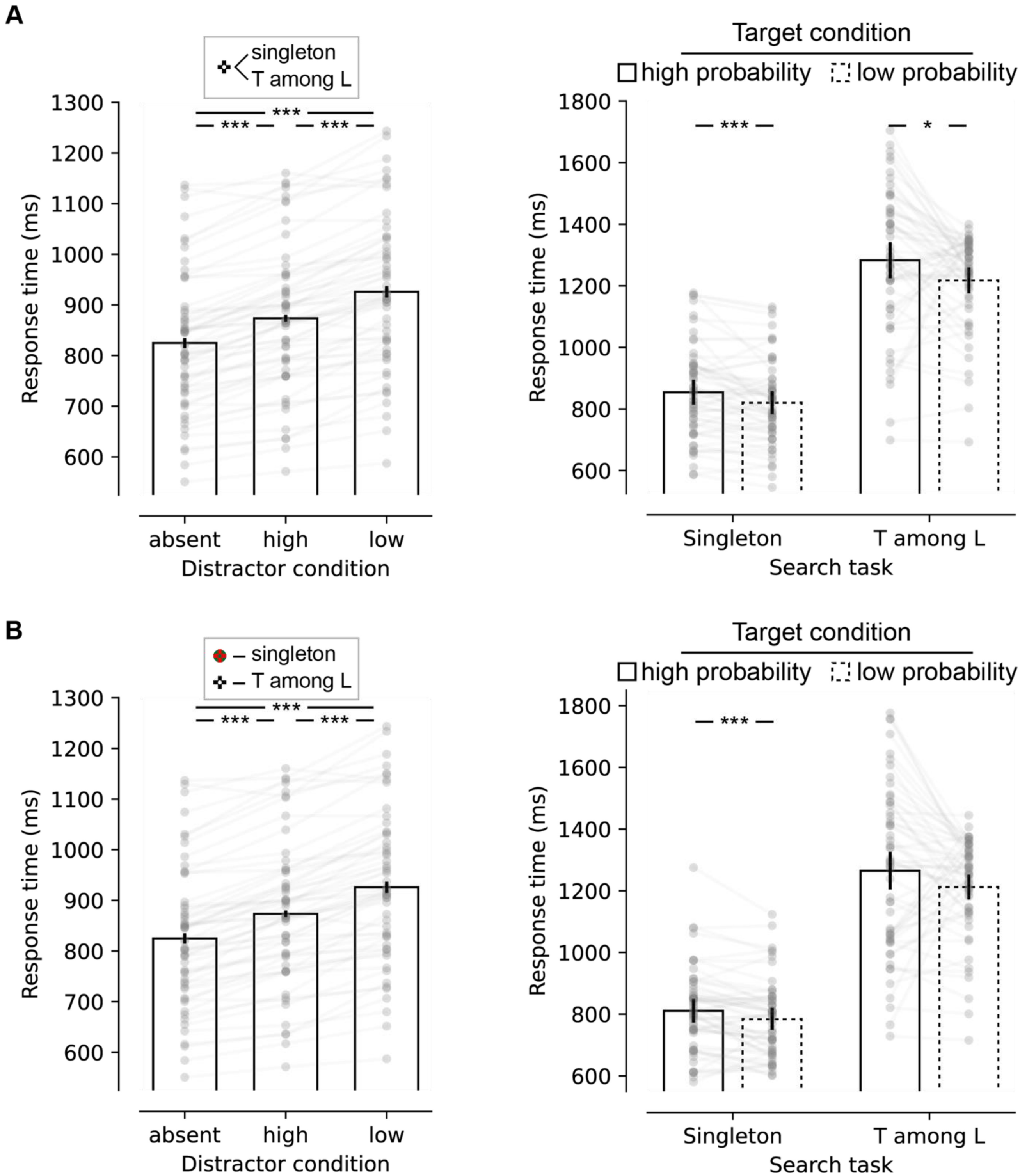
Results

To examine whether suppression learned during singleton task also remained in place during a T-among-L task, when that search was conducted serially rather than in parallel as in Experiment 1, we conducted the same analysis as in Experiment 1. As shown in Figure 3 (left panels in subplots A and B), the main effect of distractor condition, $F(2, 179) = 335.5$, $p < .001$, $\eta_p^2 = .75$, in both experiments, $F(2, 85) = 172.8$, $p < .001$, $\eta_p^2 = .76$ in Experiment 2A; $F(2, 93) = 163.6$, $p < .001$, $\eta_p^2 = .75$ in Experiment 2B, again reflected a gradual increase in RTs across the three conditions. Specifically, distractors reliable slowed down responses at both low, $t(55) = 15.08$, $p < .001$, $d = 2.02$ in Experiment 2A; $t(56) = 14.96$, $p < .001$, $d = 1.98$, and high-probability locations, $t(55) = 11.51$, $p < .001$, $d = 1.54$ in Experiment 2A; $t(56) = 8.78$, $p < .001$, $d = 1.16$ in Experiment 2B, relative to the no distractor condition. Critically, however, there was also a difference between high and low-probability locations, with distractor interference being least pronounced at high-probability distractor locations both when tasks varied unpredictably in Experiment 2A, $t(55) = 10.30$, $p < .001$, $d = 1.38$, and when they were cued in Experiment 2B, $t(56) = 11.72$, $p < .001$, $d = 1.55$. As in Experiment 1, the numerical trend reflecting overall faster RTs in the cued variant of the task did not reach significance ($F = 2.17$, $p = .14$).

Unlike Experiment 1, overall RT was now reliably slower in the T-among-L task relative to the singleton task, main effect task: $F(1, 111) = 504.8$, $p < .001$, $\eta_p^2 = .82$, consistent with the notion that the T-among-L task required a more serial search process. Critically, however, as visualized in Figure 3 (right panels in subplots A and B), despite this clear difference in search strategies between search displays, there was again clear evidence that learned

[1] Due to counterbalancing errors, in Experiment 2A, one location (top left) served as high probability location eight times, and as a result another location (top) six times, whereas in Experiment 2B, the planned sample size was exceeded by one (bottom and left location served as high probability location eight times and the top right served as high-probability location six times).

Figure 3
Learned Spatial Suppression Also Transfers From Parallel to Serial Search



Note. (A) Mean RT in the singleton task as a function of distractor condition (left plot) and as a function of search task (singleton task, T-among-L task; right plot) and target condition (high probability and low probability) in Experiment 1A, where tasks varied unpredictably. (B) The same analysis was demonstrated in Panel A, using data from Experiment 2B, where the fixation marker signaled the upcoming search task such that it could be anticipated. RT = reaction time. See the online article for the color version of this figure.
* $p < .05$. *** $p < .001$.

suppression impaired target processing at the high-probability distractor location irrespective of the task at hand as reflected by a main effect of target condition, $F(1, 111) = 17.5$, $p < .001$, $\eta_p^2 = .14$; $F(1, 55) = 11.08$, $p = .002$, $\eta_p^2 = .17$ in Experiment 2A; $F(1, 56) = 6.7$, $p = .012$, $\eta_p^2 = .11$ in Experiment 2B, in the absence of reliable interactions (all Fs < 2.2, all ps $> .15$). Planned pairwise comparisons confirmed that the difference in target responses differed between high and low-probability locations not only in the singleton task, $t(55) = 3.40$, $p < .001$, $d = 0.45$ in Experiment 2A; $t(56) = 3.23$, $p = .002$, $d = 0.43$ in Experiment 2B, but the same difference was also observed in the T-among-L task, although it should be noted that while this effect was reliable in Experiment 1A, $t(55) = 2.47$, $p = .017$, $d = 0.33$, it failed to reach significance in Experiment 1B ($t = 1.86$, $p = .069$).

Together, these findings demonstrate that transfer of learned spatial probabilities as observed in Experiment 1 is not restricted to conditions where both search tasks rely on the same search mode, but instead, it also generalizes to search tasks with another search strategy. Similar to Experiment 1, there was again little evidence that this generalization across tasks should be attributed to explicit knowledge about the regularity, as out of the 15 participants (eight in Experiment 2A and seven in Experiment 2B) who indicated that they noticed the spatial imbalance, only three (two in Experiment 2A and one in Experiment 2B) correctly identified the high-probability location.

Across Experiment Analysis

The previous results convincingly demonstrate that distractor suppression learned in one task, the singleton task, generalized to another search task without visual distractors, irrespective of whether the search strategy adopted in that task and whether task switches could be anticipated. At the same time, it should be noted that counter to previous studies examining transfer of probability cuing (Britton & Anderson, 2020; Jiang et al., 2015), here we relied on an intermixed design leaving open the possibility that the effect of interest was largely driven by intertrial repetition effects rather than reflecting learning across longer time scales (Maljkovic & Nakayama, 1994). To address this in an analysis collapsed across all four experiments we examined how intertrial repetitions related to location priming and task switching affected the transfer. We chose to collapse across all experiments given that the observed pattern was the same across all experiments and the number of trials in which the target in the T-among-L was preceded by a singleton distractor on that same location was relatively low ($N = \sim 4$ for low-probability locations; $N = \sim 6$ for high-probability locations). As visualized in Figure 4A, a repeated measures ANOVA using only the T-among-L data with within-subject factors distractor to target priming (yes, no) and target condition (high, low) yielded no reliable interaction, $F(1, 211) = 0.022$, $p = .88$; Bayes $\text{Factor}_{\text{excl}} = 8.58$, reflecting that the observed transfer was reliable both when a target was preceded by a distractor at the same position in the singleton task, $t(211) = 2.15$, $p = .032$, $d = 0.15$, and when it was not, $t(224) = 3.37$, $p < .001$, $d = 0.23$. Similarly, the same analysis yoked to the factor task switch (switch, no switch; see Figure 4B), which showed a clear switch cost, main effect task switch: $F(1, 224) = 7.16$, $p = .008$, $\eta_p^2 = .031$, also yielded no interaction, $F(1, 224) = 0.093$, $p = .76$; Bayes $\text{Factor}_{\text{excl}} = 9.16$, reflecting that the effect was reliable irrespective of whether the task switched, $t(224) = 3.46$, $p < .001$, $d = 0.23$, or repeated, $t(224) = 3.45$, $p < .001$, $d = 0.23$. Together, these findings demonstrate that the observed transfer across experiments was unlikely to be driven by attentional biases stemming from the immediately preceding trial, but instead arguably reflect learning across longer time scales, although it cannot be excluded that the effects at least in part reflect lingering effects from more distant trials in the past (Talcott & Gaspelin, 2020).

Based on the exit questionnaire, there was little evidence that the generalization across tasks can be attributed to an explicit strategy with only a relatively small subset of participants being classified as aware of the distractor imbalance. To test this, we used the responses on the exit questionnaire to create two groups, with the split either being based on whether participants indicated having noticed the spatial imbalance (37 vs. 188), participants indicating the correct regularity location (60 vs. 165) and having both noticed the regularity and selecting the correct location (12 vs. 213) and included this as a between-subject factor in the comparison between high and low-probability locations in the transfer task. None of these exploratory splits yielded any evidence that the effect was driven by explicit knowledge regarding the regularity (all ps $> .42$, all Fs < 0.67). Although this does not rule out the possibility that participants had some explicit knowledge regarding the underlying manipulation (Vadillo et al., 2020), the lack of a difference between these two exit questionnaire-based groups strongly suggests that the observed transfer should be attributed to learning, possibly implicitly, rather than an explicit strategy to downweigh the location with a higher distractor probability in the singleton task.

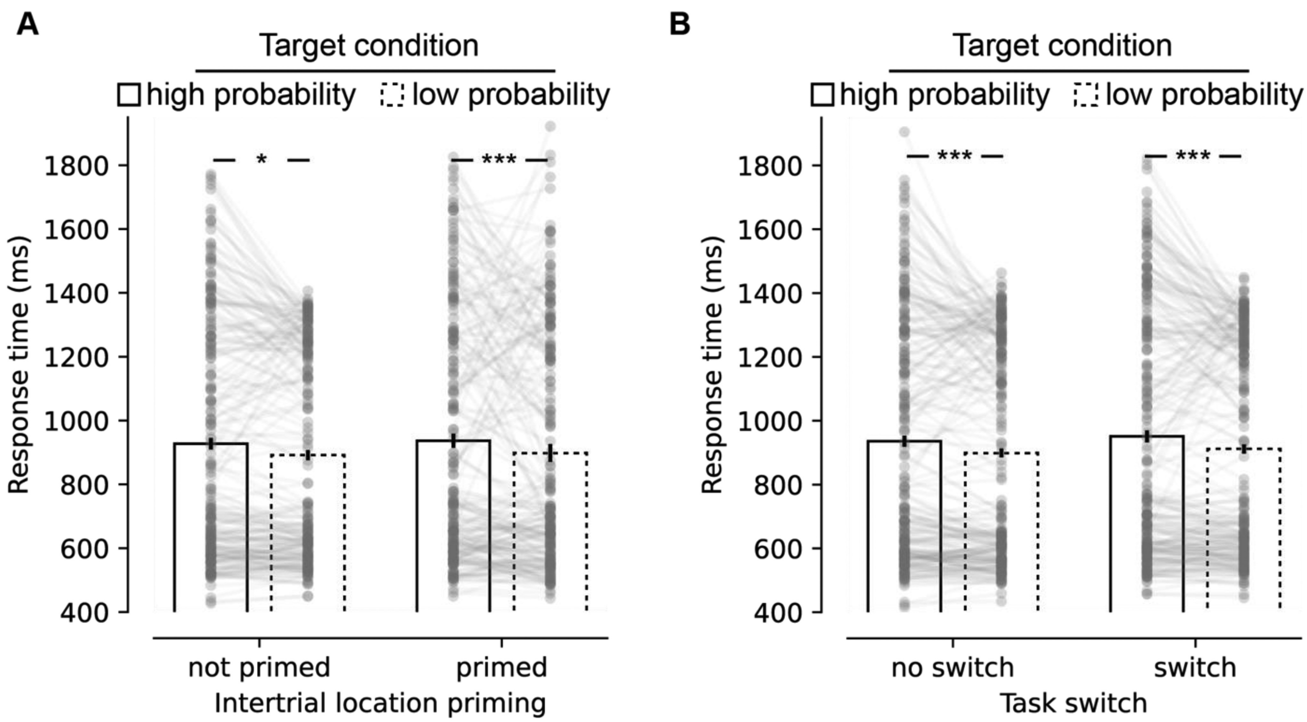
General Discussion

A recent line of research has shown that human observers are sensitive to spatial imbalances of salient singleton distractors across displays, such that distractor interference is reduced and target processing impaired at locations with a higher distractor probability (Theeuwes et al., 2022). Although the characteristics of this effect have been relatively well characterized, it remains unclear whether suppression learned in one task will generalize to another task. The current study was designed to study whether learned suppression would generalize to a task without salient visual distractors. Results clearly show that there is transfer of learned spatial suppression from the additional singleton task to a T-among-L task regardless of whether that latter search involved parallel search (the T pops out among the Ls; Experiment 1) or whether search for the T is slow and serial (Experiment 2). Moreover, this transfer was observed both when the tasks switched randomly, and when a central cue allowed participants to anticipate the upcoming search task. Overall, these findings suggest that implicit learned biases are rather inflexible as they stay in place when there is a dramatic change in the search strategy required and even when participants can anticipate the upcoming search and/or when that same search was repeated.

On the one hand, the current findings are remarkable as implicit learning has been characterized as inflexible and largely tied to the context in which it was acquired with little to no transfer across tasks (Abrahamse & Verwey, 2008; Dienes & Berry, 1997). For example, if during sequence learning, the underlying statistical structure remains the same but the surface features change (e.g., from one set of letters to another; Dienes & Berry, 1997) or when a superficial change embeds the serial reaction time task (SRT)

Figure 4

Difference Between High- and Low-Probability Locations Within the T-Among-L Task Using Data From All Four Experiments



Note. (A) Mean RT in the T-among-L task as a function of target condition (high probability and low probability) separate for trials where the target was preceded by a distractor on the same location (primed) or not (not primed). (B) The same analysis was demonstrated in Panel A, but now separate for trials in which the same task was repeated at least one time (no switch) or when the task was different from the preceding search task (switch). RT = reaction time. * $p < .05$. *** $p < .001$.

within a spatial selection task (Jiménez et al., 2006), there is little to no transfer. On the other hand, the one study that examined the transfer of learned spatial enhancement (via probability cueing) (Geng & Behrmann, 2002) showed robust transfer from one task to another as long as both tasks relied on serial search and when no other salient cues were available (Jiang et al., 2015). Here we extend those findings by not only demonstrating that learned suppression also transfers from one task to another, but that this transfer is even observed when the other search task requires a completely different search strategy. It is evident that in the two experiments, a completely different search strategy needed to be employed. Indeed, in Experiment 1, the "parallel" T-among-L task was highly efficient with a mean RT of about 600 ms, while the "serial" T-among-L employed in Experiment 2 was significantly slower with a mean RT of about 1,300 ms. Nevertheless, one could argue that compared to the singleton task, even the serial T-among-L task, albeit being slower, was a less effortful search as there were no singleton distractors and, in contrast to the singleton task, the target shape remained static across trials. In this respect, it is noteworthy that although learning is often task-specific within the SRT literature, transfer has been observed when the transfer task required less cognitive control than the learning task (Vaquero et al., 2020). Further research however is necessary to establish whether such an account, which predicts asymmetrical transfer effects from one task to another, also applies within the context of spatial probability learning.

At this point, one can only speculate about the mechanism that allows for the observed transfer. Within the framework of plastic changes in priority maps of space following statistical learning (Ferrante et al., 2018; Theeuwes et al., 2022), one has to assume that the transfer reflects relatively stable changes to the attentional priority map. This inability to flexibly adjust learned priority settings in response to task changes is consistent with the finding that learned suppression generalizes across different contexts (Britton & Anderson, 2020; de Waard et al., 2022). Together these findings suggest that changes in attentional priorities in response to distractor regularities result from a rather robust learning mechanism that groups information across a set of independent search episodes irrespective of the context in which learning took place, or as shown here, the search task that is currently performed.

An ongoing debate in this literature centers around the question whether suppression at the high-probability distractor location is implemented proactively, or that the location only becomes suppressed after attention has been captured by the irrelevant salient distractor (i.e., reactive suppression). In support of proactive suppression, it has been demonstrated that neural excitability, as indexed by frequency tagging, is reduced at high-probability locations (Ferrante et al., 2023). Also, not only distractors, but also targets that appear at the high-probability distractor location, have been shown to elicit a contralateral early positivity (van Moorselaar et al., 2021; B. Wang et al., 2019), an event-related potential in the electroencephalography signal labeled the P_D that has been associated with suppression (Gaspelin et al., 2023; Hickey et al., 2009). Behaviorally, evidence in support of proactive suppression comes from paradigms that combine search and probe trials showing that the behavioral benefit in the search trials at high-probability distractor locations is accompanied by a probe detection cost at that same location (Huang et al., 2021, 2022, 2023). The current findings that show a transfer of the suppression to a different task appear fully consistent with this notion of proactive suppression. Indeed, because the location is already suppressed before the search display comes on, regardless which task needs to be performed, the suppressed location competes less for attention than all other locations. At the same time, it should be noted all evidence in support of proactive suppression comes from paradigms where the dependent variable, be it a neural measure of probe RTs, was measured in response to either the onset of a probe display (presented before the search display) or the onset of the search display itself. This leaves open the possibility that attention was first shifted to the high-probability location and then (rapidly) disengaged (Theeuwes et al., 2000). Indeed, the one study that did not use a prestimulus probe display, found evidence in support of initial selection of the high-probability distractor location (Chang et al., 2023). Although it is not immediately clear in what way reactive suppression could account for the present findings, future research is necessary to establish how suppression, if at all, is implemented before search display onset. This issue is complicated by evidence that learned suppression may not evident in active neural firing, but instead be implemented via a latent synaptic mechanism (Duncan et al., 2023; van Moorselaar & Slagter, 2020).

It is important to note that the suppression effect is not only found immediately following the switch from performing the additional singleton task to the T-among-L task but also stayed in place on the next T-among-L trial. This implies that even executing a completely different task is not cue to abandon the previously learned attentional priority setting, not even when the upcoming search task was cued by means of a 100% valid cue, providing additional evidence for the robustness of the learned attentional priority settings across tasks. This inability to adjust priority settings across tasks appears inconsistent with findings from a recent study by Zhang and Carlisle (2023), in which explicit search goals could unlock learned spatial biases on a trial-by-trial basis. In that study, across experiments, participants were instructed to search for four potential target objects, each of which had its own unique high-probability location. Based on the findings, the authors concluded that learned spatial priority maps can be selectively prioritized based on the current search goals. In addition to the difference between the paradigms used, it should be noted that Zhang and Carlisle (2023) investigated dynamic target regularities, whereas here we focused on static regularities regarding the distractor. Indeed, we have recently shown that while participants are able to implicitly learn across-trial regularities regarding target locations (Li & Theeuwes, 2020), such across-trial statistical learning does not extend to the location of salient distractors (Li et al., 2023). One relevant construct when studying such dynamic regularities, is the successor representations, a neural representation of the current state in terms of its future (successor) states (Stachenfeld et al., 2017). Although highly speculative one could thus account for the apparent discrepancy by assuming that successor representations can entertain different priority maps, but only when the future representation is relevant for the task at hand. In such a perspective implicit learned biases regarding distractors may be rather inflexible, whereas task-relevant regularities can be dynamically adjusted in response to the current successor representation.

In sum, we conclude that learned spatial suppression generalizes to a completely new task, even when the switch to that new task, which does not require suppression, can be predicted. We propose that learning about distractor regularities at the spatial level results in the formation of an inflexible priority map, which remains active even when participants switch from parallel to serial search.

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